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Adjustments for improved upper arm adjustment factor in REBA and RULA methods based on postural sway analysis

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ABSTRACT: Ergonomic risk assessment methods are widely utilized in the construction sector to mitigate work-related musculoskeletal disorders (WMSDs). However, current methods, such as the Rapid Entire Body Assessment (REBA) and the Rapid Upper Limb Assessment (RULA), often encounter issues related to overestimation and fluctuation, primarily due to sharp boundaries defined by ambiguous terms. Specifically, a 0° threshold is frequently used as a strict boundary for adjustment factors, disregarding minor joint movements and muscle activation. This study aims to quantify the upper arm-related risk adjustment factors in REBA and RULA by analyzing angle tolerances through muscle activation data. Angle tolerances are derived using surface electromyography (sEMG) data from specific muscles during arm abduction movement. A total of 23 participants' data are used for this study. The main results include 1) revealing 0° threshold is unsuitable as an adjustment boundary through muscle activation analysis before arm abduction. 2) identifying joint tolerance defined by the endurance limit of 10% maximal voluntary isometric contraction (%MVC). Finally, these tolerances are subsequently used to refine posture categorization within the risk rating adjustment process, resulting in a modified upper arm adjustment factor in the REBA and RULA frameworks, which incorporates posture sway for more accurate risk estimation. The outcomes of this study are expected to mitigate the overestimation and fluctuation issues inherent in REBA and RULA while introducing a novel integration of muscle status and risk detection for risk assessment.

1. INTRODUCTION

Despite advancements in automation through Industry 4.0, the physically demanding nature of construction work and its dynamic task requirements continue to make it a high-risk environment. Consequently, workers face an increased likelihood of developing work-related musculoskeletal disorders (WMSDs) [1]. In Canada alone, 18,131 work-related injuries were documented in 2022, marking a 10.9% increase from the previous year [2]. Beyond posing direct risks to worker health and safety, WMSDs contribute to higher absenteeism rates and impose substantial financial burdens on the construction industry [3]. Therefore, to foster a safer and more sustainable work environment, it is imperative to accurately assess and mitigate ergonomic risks associated with construction tasks.

Several ergonomic risk assessment methods have been developed to address the risk factors associated with WMSDs. The most widely utilized approaches include the Ovako Working Posture Analysis System (OWAS) [4], Rapid Upper Limb Assessment (RULA) [5], and Rapid Entire Body Assessment (REBA) [6]. While these methods provide systematic frameworks for risk identification, their reliance on rule-based evaluations conducted through expert observations introduces limitations regarding both cost-effectiveness and accuracy [7-9].

To enhance the accuracy and effectiveness of ergonomic assessment methods, advanced technologies like motion capture (MoCap) system have been introduced to provide more precise posture data [10,11]. Moreover, IMU sensors, known for their lightweight and portable design, can be seamlessly integrated into construction clothing and have demonstrated high accuracy and repeatability in field conditions [12,13]. Beyond joint angle analysis, surface electromyography (sEMG) [14,15] enables a more comprehensive biomechanics-level analysis by detecting muscle electrical activity.

However, the effectiveness of risk evaluation is still constrained by inherent limitations in widely used assessment methods such as REBA and RULA [16,17]. Current posture categorization for risk rating adjustments relies on ambiguous descriptors, such as "abducted" versus "not abducted" [5,6]. These classifications often assume an ideal boundary of 0°, with no tolerance for natural variation when determining adjustment factors. This rigid scoring method overlooks the practical realities faced by construction workers, whose anatomical structure and natural postural sway make it impossible to consistently maintain a 0° body joint angle [18,20]. As a result, ergonomic assessment outcomes are prone to overestimation and fluctuation, particularly during continuous movements. Advanced motion detection techniques, which measure joint angles with decimal-level precision, can exacerbate this issue.

In response to this limitation, this study proposes modifications to the REBA and RULA methods by integrating sEMG signal analysis in postural sway experiments. The study is structured into two key phases: (1) determining shoulder joint tolerance for the adjustment risk rating process through the analysis of muscle activation patterns and (2) developing a revised ergonomic risk assessment framework that incorporates joint tolerances into the adjustment risk rating process. The outcomes of this study are expected to mitigate the overestimation issues inherent in REBA and RULA while introducing a novel integration of muscle status and risk detection, thereby providing a more accurate and comprehensive approach to ergonomic assessment.

2. RELATED WORK

This section provides a comprehensive review of ergonomic risk assessment approaches, tracing their development from traditional methods to advanced technologies.

2.1 Conventional approaches for ergonomic risk assessment

Several rule-based observational assessment methods are widely used globally, including the OWAS [4], RULA [5], and REBA [6]. OWAS evaluates risk levels across different body segments by assessing workers' awkward postures in manufacturing environments. Whereas RULA specifically focuses on calculating joint angles to determine risk scores for upper limb movements, REBA expands this approach by incorporating full-body posture analysis into its assessment framework. These rule-based assessments fundamentally depend on accurate posture descriptions as their primary input, rendering the precision of collected posture data essential for the reliability of assessment results [7,21]. However, when joint angles approach category boundaries, observers may struggle to distinguish between risk levels, leading to inconsistencies and intra-/inter-observer reliability issues [22]. Additionally, rule-based observational methods are time-intensive and costly due to the reliance on manual assessment [23]. Given these limitations, conventional approaches require improvements to enhance their efficiency and accuracy.

2.2 Advanced technologies for ergonomic risk assessment

A wide range of advanced technologies has been utilized to detect risk factors associated with WMSDs for construction workers. The following two main categories are mainly discussed: 1) approaches that enhance the accuracy of joint angle measurements by leveraging MoCap system; 2) approaches that focus on physiological data to assess risk at the biomechanical level.

The first type of approaches builds upon the fundamentals of rule-based ergonomic assessment methods by providing more objective and accurate joint angle inputs while automating the evaluation process. These implementations primarily utilize MoCap system to obtain precise joint coordinates. MoCap-based methods

include IMU and optical MoCap. IMUs are designed to measure acceleration, angular velocity, and, in certain instances, magnetic field strength. The compact, lightweight, and high-capacity nature of IMUs makes them particularly suitable for human activity recognition and the prevention of WMSD [24,25]. Humadi et al. experimentally investigate the validity of RULA assessment using IMUs, reporting a minimum mean error of approximately 0.3° for upper-arm flexion among all measured joint angles [26]. However, the requisite skin-tight sensor attachment for noise reduction may restrict natural movements and impair work efficiency in construction settings. [27].

The optical MoCap system represents an alternative approach for collecting highly accurate joint angle data. This system uses multiple calibrated cameras to track reflective markers on a subject, capturing their 3D spatial and temporal coordinates from various angles for motion reconstruction [28]. As a result, the accuracy of such a system can reach millimeter-level precision [29]. However, optical MoCap systems are constrained by high costs, sensitivity to lighting conditions, and the need for a controlled environment, which limits their application in outdoor measurements for construction tasks [30].

The second type of approaches relies on direct measurements using physiological sensors to monitor the physical status of the human body. For instance, sEMG is crucial for muscle activity analysis because it provides electrical activity of muscles during contraction and relaxation, offering valuable insights into muscle control function and the loads experienced by tissues and joints [31]. Although it cannot measure kinematics data, as a non-invasive method, sEMG signal can be used to predict muscle activity and muscle fatigue. A variety of signal analysis techniques are employed to extract meaningful fatigue-related information from raw EMG data. Amplitude-based metrics, such as root mean square (RMS) and mean absolute value (MAV), reflect a decline in force production as muscles fatigue. Similarly, frequency domain analyses, including power spectral density, capture shifts in the EMG spectrum toward lower frequencies during sustained or fatiguing contractions [15,32,33]. Ranavolo et al. determine the sEMG-based indices of 12 trunk muscles to evaluate the danger of lifting tasks [34]. Johns et al. examine the agreement between 5 ergonomic risk assessment methods by recording sEMG during 4 sawmill tasks [35].

Although these advanced MoCap-based methods provide accurate joint angles input for ergonomic risk assessment tools, the evaluated risk score will suffer from overestimation and fluctuation issues due to the intrinsic drawbacks of the adjustment risk rating process. To address this limitation, this study investigates the tolerance for adjustment factors by analyzing muscle activation during body segmental movement. A postural sway-incorporated ergonomic risk assessment method is then developed to alleviate the overestimation and fluctuation issues in the current REBA and RULA systems.

3. METHODOLOGY

Workflow of this study is presented in Fig. 1. This methodology part will discuss data acquisition and experiment procedure.

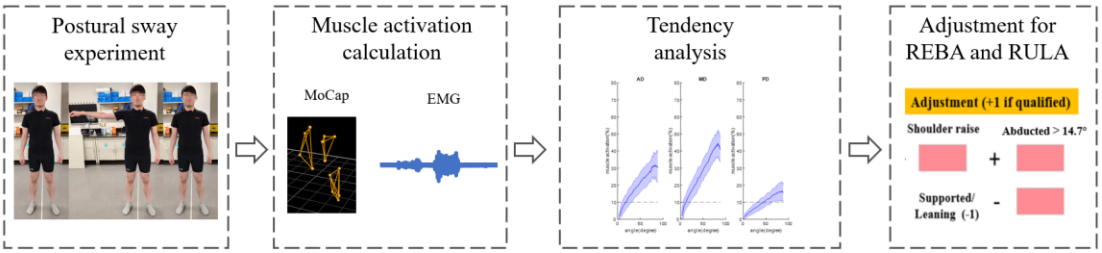

Fig. 1: Workflow for developing postural sway-incorporated ergonomic risk assessment method.

3.1 Data acquisition

This study primarily focuses on the adjustment factors for the upper arm. Consequently, arm abduction was selected for investigation. These movements were performed at the Syncrude Centre at Glenrose

Rehabilitation Hospital and the Occupational Ergonomics Research Lab at the University of Alberta. In total, twenty-five right-handed subjects (15 male, 10 female) were recruited from the student population from the university. The subjects aged between 21 and 32 years, with body mass ranging from 52 to 86 kg and no history of injury to the relevant body parts. Prior to the experiments, the procedures and potential risks were explained, and informed consent was obtained. Ethics approval was granted by the University of Alberta (ethics approval: Pro00129961).

Three sEMG electrodes were placed on the right arm to record electrical muscle activity, representing muscle activation across the following muscles: the anterior deltoid (AD), middle deltoid (MD), and posterior deltoid (PD). Prior to the experiments, the areas of electrode attachment were cleaned with alcohol wipes to ensure proper skin preparation. The MA300 electromyography system (10 channels) and the Delsys Trigno Centro system (14 channels) were used to collect the sEMG data. The subject's movements were recorded by Vicon MoCap system. Ten reflective markers were attached to the subject's right arm and trunk to capture joint motion during the experiment. The marker trajectories were then used to calculate the joint angles of the upper arm. Fig. 2 shows the placement of sEMG sensors and markers.

In this article, the endurance limit is assigned as the tolerance for arm abduction. The endurance limit is defined as the threshold percentage of maximum voluntary contraction (%MVC) below which a posture or static muscular activity can be sustained for an indefinite period without resulting in muscle fatigue [36]. Jørgensen et al. propose that the endurance limit for sustained contractions is approximately one hour at 10% MVC [37]. This 10% MVC value is adopted in the present study to represent the tolerance for adjustment factors.

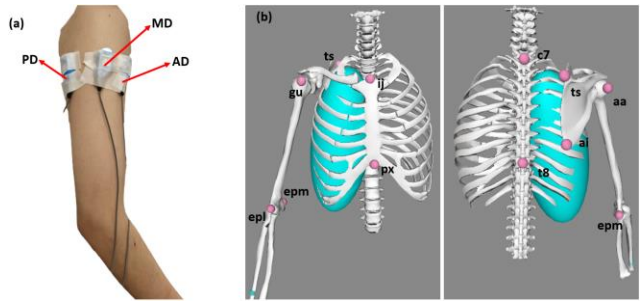

Fig. 2: (a) sEMG sensors placement; (b) markers placement.

3.2 Experiment procedure

First, three different maximum voluntary contraction (MVC) tests were performed to normalize EMG data: 1) AD: Subject flexes the shoulder to 90° with an extended elbow while resisting downward force applied to distal forearm. 2) MD: Subject abducts the shoulder to 90° in the frontal plane with an extended elbow, resisting downward force at the distal forearm. 3) PD: Subject positions the shoulder in 90° of abduction with slight horizontal abduction and resists forward-directed force on the distal forearm.

For the formal experiment, subjects were instructed to perform arm abduction. The subjects began with their right arm hanging naturally, palm facing medially, in preparation (natural posture). They then raised their right arm to a 90°, held this position for 5 seconds, and lowered it back down. The formal experiment included 5 cycles with 8-second intervals before each cycle. During the interval phase, the subjects are instructed to maintain a relaxed, neutral posture, allowing for the observation of changes in joint angles and muscle activation levels while participants remain relaxed. The joint angle and muscle activation gathered during this interval stage provide insights into baseline muscle activation and joint angle values before initiating motion. The complete experiment procedure is illustrated in Fig. 3.

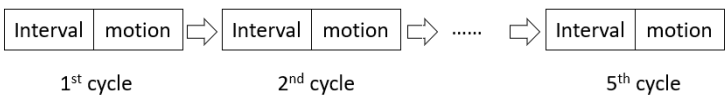

Fig. 3: Configuration of formal experiment.

3.3 Data processing

All sEMG data from the formal experiments and MVC tests were first baseline-corrected. The sEMG data were then full-wave rectified and digitally bandpass filtered (10–1000 Hz) using a second-order Butterworth filter [38]. The RMS was calculated using a 200-ms sliding window [39]. To minimize variability across channels, the amplitude of all sEMG data for each subject was normalized to the MVC value of the same muscle using the RMS amplitude measure.

For joint angle calculations, measurements were required in the sagittal, frontal, and horizontal planes. Each segment was treated as a two-ended joint and represented in vector form, shown in Eq. 1:

$$[1]\ \mathrm{V}_{\mathrm{a-b}} = \mathrm{J}_{\mathrm{a}} - \mathrm{J}_{\mathrm{b}}$$

$$[2]\ \mathrm{V}^{\mathrm{P}}_{\mathrm{a-b}} = \mathrm{V}_{\mathrm{a-b}} \cdot \frac{\mathrm{P}}{\|\mathrm{P}\|^2}$$

$$[3]\ \theta^{\mathrm{P}}_{\mathrm{ab,cd}} = \arccos\left(\frac{\mathrm{V}^{\mathrm{P}}_{\mathrm{a-b}} \cdot \mathrm{V}^{\mathrm{P}}_{\mathrm{c-d}}}{\left\|\mathrm{V}^{\mathrm{P}}_{\mathrm{a-b}}\right\| \cdot \left\|\mathrm{V}^{\mathrm{P}}_{\mathrm{c-d}}\right\|}\right)$$

Where $\mathrm{V}_{\mathrm{a-b}}$ represents the vector pointing from joint a ($\mathrm{J_a}$) to joint b ($\mathrm{J_b}$). The vectors were then projected onto the relevant planes (P), and the arc cos function was applied to compute joint angles ($\theta^{\mathrm{P}}_{\mathrm{ab,cd}}$) between the two projected vectors, shown in Eq. 2, Eq. 3. Further analyses were conducted ot obtain muscle activation-joint angle curves. For each subject, an ensemble average of 5 cycles was calculated. Then, a grand ensemble average of subjects was assembled for each muscle.

4. RESULTS AND DISCUSSION

4.1 Experiment results

The RMS parameter represents the average intensity of the EMG signal, providing an overall measure of muscle activation. Therefore, muscle activation for each muscle is quantified using RMS, which is calculated over the entire motion window. The RMS results for arm abduction are presented in Fig. 4. The numbers in brackets indicate the number of subjects included for each specific muscle. A lower sample size for certain muscles results from EMG electrode displacement during the experiment or the muscle not being sufficiently active.

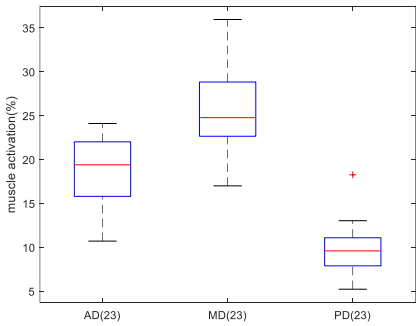

Fig. 4: Overall muscle activation in arm abduction.

For the average intensity of the EMG data, all selected muscles generally exhibit lower activation levels. During arm abduction, the highest average activation is observed in MD at 24.77% MVC. However, the PD showed an activation level of 9.59% MVC, which doesn't exceed the 10% MVC endurance limit. These results suggest that the muscles involved don't need to exert significant force during the arm abduction, as

participants perform the movements without additional weight and at a self-selected, comfortable speed. These controlled conditions are designed to replicate the 0 Force/Load scenario in REBA and RULA.

To visually analyze changes in muscle activation throughout the entire movement, the grand ensemble averages of all participants are computed and examined for each muscle. These averages offer a comprehensive perspective on muscle activation patterns across various joint and body segment movements. Such findings contribute to research on joint boundaries and tolerance definitions in REBA and RULA, as these scoring frameworks primarily rely on body posture assessments. Fig. 5 illustrates the muscle activation–joint angle relationships for arm abduction, with grand ensemble averages and their standard deviations displayed.

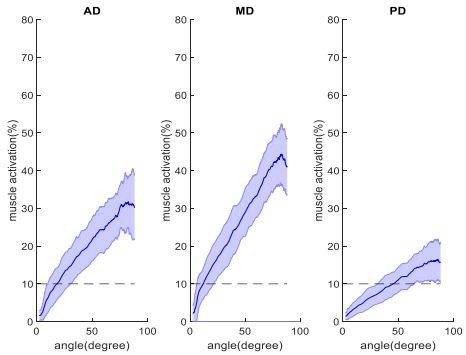

Fig. 5: Muscle activation–joint angle relationships for arm abduction.

There are several common trends observed across the three movements. Muscle activation consistently increases as joint angles increase, with peak activation occurring before reaching the maximum joint angle, followed by a subsequent decrease. Although the specific joint angle at which activation exceeds 10% of MVC varies, all muscles eventually surpass this threshold. Additionally, the rate of increase in activation (slope) remains relatively constant for each muscle during the rising phase of the curve. Some motion-specific findings are also noted. In arm abduction, PD exhibits a more gradual increase in activation compared to AD and MD, causing it to reach 10% of MVC later, around the midpoint of the movement. Additionally, AD and MD display a steep rise in activation at the early stage of movement (joint angles less than 10°), followed by a slower and steadier increase until reaching peak activation.

To determine the final angle tolerance for adjustment factors in REBA and RULA, the activation curves of muscles are weighted and averaged to generate a generalized intensity pattern of muscle activation in relation to joint angles. The result is illustrated in Fig. 6. For arm abduction, the contribution of the three deltoid muscles varies. While no studies have explicitly quantified the percentage contribution of each muscle, previous research suggests that MD generates significant abduction torque, accounting for up to 65% of the total torque [40]. Based on this finding, the weighting factors for the deltoid muscles are assigned as follows: AD (17.5%), MD (65%), and PD (17.5%). The joint tolerance of arm abduction is 14.7°.

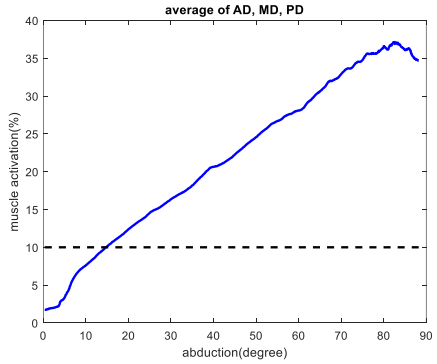

Fig. 6: Generalized muscle activation in relation to joint angle.

Natural postural sway is observed during the 8-second neutral posture phase, which is required before each subject engages in the formal motions. Table 1 shows the average joint angle values and muscle activation for each subject during this neutral posture phase.

Table 1: Average joint angle and muscle activation during neutral posture phase.

Motion	Average joint angle (degree)	*Average AD activation (%)*	*Average MD activation (%)*	Average PD activation (%)
Arm abduction	1.62	2.22	2.32	1.46

4.2 Discussion

For the interval stage, the average joint angle measurements reveal that body joints exhibit subtle movements during natural posture. While these movements are typically less than 2°, which are not easily perceptible to the human eye. However, they can be precisely captured through the use of advanced measurement devices. Given that workers' joint angles naturally fluctuate within a small range rather than remaining precisely at 0°, a physiologically impossible posture, even minor changes in joint angles result in corresponding variations in adjustment factor values. Thus, this introduces significant variability in the final results of REBA and RULA, contributing to severe fluctuation issues in the assessment outcomes. Furthermore, the average muscle activation results indicate that the relevant muscles are activated at a low level prior to the commencement of formal motion. Specifically, the activation of all muscles was below 3%, which remains less than half of the endurance limit. As a result, workers are unlikely to experience any risk under these conditions. However, this pre-activation contributes to an overestimation issue in the final assessments of REBA and RULA. For arm abduction, the tolerance is 14.72°, approximately 16.36% of the entire motion. Therefore, the potential risk, as indicated by muscle activation, emerges as early as around 16% of the total movement, rather than at the outset. Consequently, this also indicates existing REBA and RULA adjustment rating systems are inadequate and require revision.

By examining the average activation-angle curve results, several common patterns can be identified that are relevant to the new adjustment rating process. The curves exhibit a similar shape: muscle activation increases from the start, reaching a peak value before the peak joint angle, and then decreases. To understand the behavior of these curves, two parameters—slope and peak activation value—are analyzed. The slope represents the rate of change in muscle activation. Before the peak activation point, the curves always show an upward trend, with a steeper curve indicating a rapid increase in activation, which could signal potential danger. For arm abduction, the curve slope is relatively gentle at the beginning of the movement but becomes steeper between 4° and 9°. After this point, the slope remains moderate until reaching the peak activation. Although there is a noticeable slope change during the early phase, it is important to note that the activation level during this phase remains below 10%, indicating a safe range for workers. Therefore, a detailed categorization of risk based on slope change is unnecessary for arm abduction.

While the MVC% value does not directly reflect the degree of danger for workers, it serves as an indicator of muscle activation intensity. High MVC% movements can lead to more rapid muscle fatigue. Sustained high-intensity contractions deplete energy reserves and accumulate metabolic by-products, contributing to fatigue [41]. The peak activation value represents the maximum intensity of the movement and can be used to assess the potential for muscle fatigue. The average muscle curves show a peak activation value below 40%, which is considered indicative of low-intensity tasks. Consequently, establishing a detailed risk classification based on the peak activation value is not necessary. Considering that this study focuses on adjustment factors, a simpler binary rule (+1 for any abduction) is sufficient for evaluating potential risks.

4.3 Revised REBA and RULA

Due to the presence of postural sway, the adjustment factor risk score definitions in the original REBA and RULA models suffer from overestimation and fluctuation issues, as they overlook minor joint movements.

Based on endurance limit values, this study determines shoulder joint angle tolerance by focusing on the muscle activation performance of muscles associated with arm abduction. The consistent slope and lower peak activation values indicate that a binary rule based on joint angle tolerance is sufficient to assess potential risks when calculating the adjustment factor. The revised REBA method (upper arm adjustment factor) is illustrated in Fig 7.

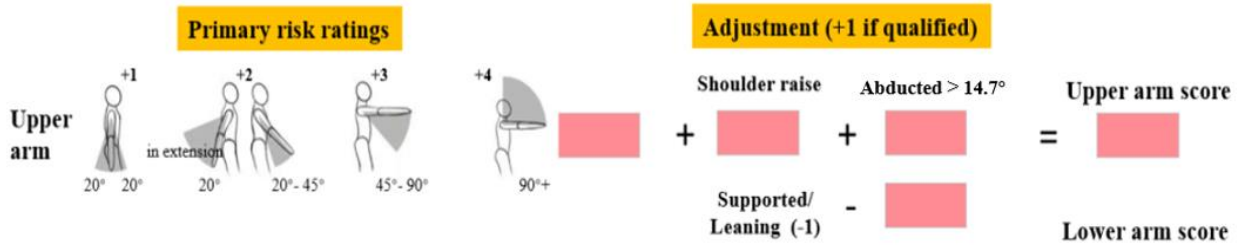

Fig 7: Revised REBA method (upper arm adjustment factor)

4.4 Limitation

Although the postural sway-integrated REBA and RULA address overestimation and fluctuation issues, several limitations have still been identified. 1) Limitations in the choice of subjects and tasks. Expanding the sample size is crucial to further investigate the potential relationships between mobility, gender, and age. In addition, future studies will involve construction workers as participants to collect data reflective of real-world practices. Joint tolerances also should be evaluated across different types of construction tasks to determine whether task-specific differences require adjustments to joint tolerances. 2) Limitations in the number of selected muscles. Three muscles were selected for arm abduction to represent muscle activation intensity through changes in MVC%. However, these muscles may not fully represent the corresponding motion. Future work could involve conducting detailed experiments that measure the muscle activity of additional muscles involved in these movements. 3) Limitations in joint angle categories. The experiments primarily focus on adjustment factors related to the upper arm due to the limited time. However, REBA and RULA also include adjustment factors for the neck and trunk. To develop a comprehensive risk assessment method, future research should investigate the remaining adjustment factors and establish primary score boundaries for the arm, wrist, neck, and trunk.

5. CONCLUSIONS AND FUTURE DIRECTION

This study primarily contributes to the field of occupational health and safety management for construction workers by developing revised ergonomic risk assessment methods based on the current REBA and RULA systems. These revised methods provide a more accurate evaluation of potential risks associated with construction tasks. It addresses the inherent limitations of existing assessment methods, which are often characterized by overestimation and fluctuation due to rigid adjustment factor boundaries that fail to account for joint tolerances and overlook natural postural sway. To overcome these limitations, this study analyzes the activation levels of relevant muscles to determine the joint angles corresponding to the endurance limit, which are then used as the tolerance for adjustment factors. The methodology consists of two main steps: (1) identifying joint tolerances based on muscle activation changes from arm abduction experiments, and (2) developing the revised postural sway-integrated REBA and RULA methods.

The joint angle and muscle activation results during the interval stage highlight the common occurrence of postural sway in the shoulder, which contributes to overestimation and fluctuation issues in traditional REBA and RULA methods. By assessing the joint angle corresponding to the endurance limit, this study provides a biomedical perspective to enhance ergonomic risk assessments. Although the postural sway-integrated REBA and RULA address overestimation and fluctuation issues by accounting for minor joint movements in comparison to the traditional REBA and RULA methods, several limitations have still been identified. 1) Limitations in the number of subjects: A total of 25 subjects participated in this experiment. However, due to challenges with EMG sensor attachment and motion capture data processing, data from fewer than 25 subjects were ultimately available. Consequently, expanding the sample size is crucial to further investigate

the potential relationships between mobility, gender, and age. 2) Limitation in MoCap data errors. Inherent errors arise in the gap-filling process, as it relies on estimates derived from the quality of the surrounding data. Moving forward, a more comprehensive ergonomic risk assessment model that incorporates postural sway should be developed. This model will also address limitations related to the number of subjects and MoCap data errors by expanding the participant pool and utilizing additional motion capture cameras to enhance data accuracy.

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